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VALIDATION OF FCOM PROFILES FOR AIRCRAFT ENGINE FLIGHT DATA USING NEURAL NETWORKS

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ABSTRACT

This paper explores the application of artificial neural network approach for aircraft engine health monitoring. The Digital Flight Data Recorder (DFDR) has volumes of data which if mined appropriately can provide valuable information about the aircraft health. The Flight Crew Operating Manual (FCOM) lays down operational profiles, which are recommended to be followed for efficient fuel usage and for minimizing maintenance effort. In the proposed system, the information from FCOM profiles and 'known' flight data has been fused to train a backpropagation feed-forward neural network. The predictions made by the neural network regarding the expected data of required engine parameters have been used to monitor the flight data and diagnose the health of the aircraft engine in relevance to the FCOM profiles. A Matlab GUI has been developed to simulate the 'unknown' flight data through a Simulink model for the neural network. Data from the A320 family of aircrafts has been used for training and simulating the model and preliminary results are detailed in the paper. The simulation results exhibit that the data used is fairly healthy and show a very low level of severity of degradation with respect to the profiles studied.

Key Words: Aircraft engine, FCOM, profile, flight data, neural network

NOMENCLATURE

CAS	Calibrated Air Speed
EGT	Exhaust Gas Temperature
EHM	Engine Health Monitoring
FCOM	Flight Crew Operating Manual
FDM	Flight Data Monitoring
DFDR	Digital Flight Data Recorder
FF	Fuel Flow
FL	Flight Level
GUI	Graphical User Interface
N1	Speed of LP compressor /turbine
N2	Speed of HP compressor /turbine
RMSE	Root Mean Square Error
TLA	Throttle Lever Angle

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1. INTRODUCTION

Flight Data Monitoring (FDM) is an indispensable, non-punitive, risk management tool that allows operators to identify threats and mitigate risks, thus leading to better flight safety and efficiently managed timely maintenance.

FDM during the flight is the very basic level of diagnosis. Flight Data Recorder has voluminous data and in practice hardly fifty percent of data is being analyzed. If looked at carefully, tremendous amount of information can be extracted for the analysis and diagnostics of aircraft components.

Engine and its sub-systems are the most critical systems of an aircraft. So, engine data analysis and hence monitoring the health of the engine, leads to safer flights. It not only helps in avoiding premature part removal but also caters to timely maintenance, irrespective of the statistically estimated maintenance schedules. The system being explained here is purely a ground-based system where all the processing is being taken up offline. The proposed system is part of a larger and more sophisticated Integrated Vehicle Health Management System being proposed in NAL, Bangalore.

The idea of validation of flight data for Flight Crew Operating Manual (FCOM) profiles has never been explored before. So an attempt has been made to investigate the potential of neural networks for Aircraft Engine Health Management System. The key issue in this method is to use the flight data as base source for the complete analysis instead of specific instrumentation for health monitoring. There are so many systems in the industry which use specific sensors and instrumentation for merely health monitoring.

2. FCOM PROFILES

The Flight Crew Operating Manual (FCOM) contains a wealth of information on the recommended operational regimes for the pilot in order to manoeuvre the aircraft safely and have better fuel efficiency. FCOM is the key manual for crew during and after flight. FCOM provides complete information about the aircraft systems, profiles and normal operating performance limits. Some profiles, which have relevance in the indication of the health of the aircraft engine, are given in Table 1, Table 2, Table 3 and Table 4.

In these tables, '*Profile*' is the name of the profile which has been extracted from the FCOM. The next row lays down the parameters of the flight data being considered during training and simulation of the Neural Network Model being proposed. The third and fourth row splits the parameter set of the second row into 2 sets – first, *Input to NN* states the parameters to be used as the input vector to the NN model and second, *Target Output* specifies the output parameter whose data is used as the target output vector during training. *Target Output* also represents the parameter whose values are predicted by the NN model during simulation with 'unknown' flight data and finally compared with the values of the same parameter from the *actual* 'unknown' flight data to estimate the deviation from the expected trend.

Table 1. Profile 1

Profile	*Altitude-Crossover Table*
Parameters Considered	Altitude, Mach Number, Calibrated Air Speed(CAS)
Input to NN	[Altitude; Mach Number]
Target Output	[CAS]

Table 2. Profile 2

Profile	*Stability of Parameters After Engine Start*
Parameters Considered	Engine rpm(N1, N2), Fuel Flow(FF), Exhaust Gas Temperature(EGT)
Input to NN	[N1; N2; FF]
Target Output	[EGT]

Table 3. Profile 3

Profile	*Protection from Fan Flutter*
Parameters Considered	Engine rpm(N1), Ground Speed(GS), Throttle Lever Angle(TLA)
Input to NN	[GS; TLA]
Target Output	[N1]

Table 4. Profile 4

Profile	*Recommended Thrust during Turbulence*
Parameters Considered	Altitude, CAS, Gross Weight(GWt), Engine rpm(N1)
Input to NN	[Altitude; CAS; GWt]
Target Output	[N1]

3. THE DIAGNOSTIC APPROACH

Neural Networks has been proposed in the system, being developed, due to the following reasons:

- Ability to learn the faulty and normal operating signatures from actual test data
- Reliable classification of faults in engines without requiring detailed system models
- A thorough neuralnetwork-based diagnostic tool requires the collection of extensive training data. NAL has a huge collection of flight data encompassing both nominal as well as faulty conditions
- Bayesian classifier is another possible approach, but the estimation of prior probabilities is a deterrent

Since the flight data itself is being used for training the neural network, no other physical model is required to simulate the target system. This proves to be an advantage in terms of the *computation time* and the *complexity of logic development*.

Another important feature of this system is that, only *existing* flight data parameters recorded by DFDR are made use of, thus demanding *no extra instrumentation* for the data used in the engine health monitoring system. A *'backpropagation feed-forward (BFF) Neural Network'* has been used for this data-driven diagnostic model.

The flight data used for developing and simulating the neural network for each profile has been taken from the flight data from A320 class of aircrafts. Depending on the parameters required for input and the target output of the Neural Network, the data is extracted and fed to the neural network.

Basically the data used for training is healthy in nature. So deviation from these values implies degradation. Once the neural network has been validated and tested, it is ready to be used for simulating the 'unknown' data. Depending on the profile being validated, the NN predicts the expected value of the engine health indicator parameter/s. This is compared to the actual value of these indicators in the flight data. The deviation is recorded and depending on the extent of deviation, the goodness of that output parameter is ascertained. If the deviation is significantly beyond an allowed confidence threshold, then it indicates the degradation of the aircraft engine.

4. MODEL DEVELOPMENT

Basically Matlab/Simulink Neural Network Toolbox has been used to create the neural network for the system. A *backpropagation feed-forward (BFF) Neural Network* has been used where basically, apart from the input and output layer, a single hidden layer with 20 neurons has been created. The *tansig* activation function has been used between the input and hidden layer, whereas, the transfer function between the hidden and the output layers is *purelin*.

Each profile maintains a metric file which holds relevant information pertaining to that particular profile parameters along with the accept-reject thresholds, the severity levels, maintenance and safety impact and so on. Once the neural network predicts the output for a given 'unknown' input, using information from the corresponding metric file and the actual data, the model determines the amount of deviation. The deviation extent gives an idea about the severity of the degradation of the data with respect to the profile. The basic architecture of the system is given in figure 1. The Neural Network model is first created by using available healthy flight data to train the network. In this, for each profile, according to the profile tables given in Table 1,2,3,4, the input and the target output data are provided for training the model. It is then tested by using some of the 'known' healthy flight data. Once the training seems to be satisfactory, the NN model is ready to be used on 'unknown' data. For the 'unknown' data, again according to the profile tables, the input data is given to the model. Depending on its knowledge, the NN model predicts the values for the output parameter for the healthy condition. A module then extracts the threshold information from the metric file for the profile being checked. Then the quantifier ascertains the deviation of the actual data of the output parameter, available in the 'unknown' data, from the predicted values of the NN model. If the RMSE is within the allowable threshold, then the profile is said to be adhered to and the components are healthy with respect to that particular profile. Finally the reports, stating the results, are generated.

The GUI used to simulate the neural network for selected profile has been developed using Matlab. A screenshot of the GUI is given in Figure 2. The Aircraft type, the Profile to be simulated and the 'new' data for simulation can be selected. Once the Simulink NN model to be used for simulation is also chosen, pressing the *Simulate NN* button in the GUI executes the NN model. Along with the RMSE, the slope and the regression coefficient of the curve fit for the points for the actual values of the output parameter in flight data plotted against the predicted values from the model, are displayed. Apart from this, a plot of the deviation of the actual values of the output parameter from flight data from the predicted values is also generated in the GUI.

The model training will be extended in the phase II for the predictive maintenance schedules of the aircraft engine and sub-systems. Typically the maintenance schedules are pre-fixed based on either number of flight hours or fixed durations. This has disadvantage in cases where the systems are operated sparingly. In such cases time-based maintenance calls for unwanted maintenance operations which affects both time and money.

With the trained system being used, the maintenance schedules could be dynamically tuned based on the system analysis using the NN.

5. ANALYSIS & DISCUSSION

The BFF Neural Network has been simulated using flight data taken from the A320 class of aircrafts. The model has been tested for four profiles.

The mean-squared error is one of the most commonly used measures of success for numeric prediction. This value is computed by taking the average of the squared differences between each predicted value and its corresponding actual value. The Root Mean-Squared Error (RMSE) is simply the square root of the mean-squared-error. RMSE has been used here to assert the accuracy of the NN predictor.

Plots of the Predicted and Actual values for the stated profiles are given in figures 3, 4, 5 and 6.

For the simulation of profile 1, when the parameter values of the ALTITUDE and MACH NUMBER from the 'unknown' flight data are given as input to the NN model, it predicts the value for the CAS parameter(Output parameter for the first profile stated in Table 1). Figure 1 displays these predicted values and the actual CAS values from the 'unknown' flight data being considered plotted against the ALTITUDE. The scale used shows that the difference between the two is within the allowable threshold.

For the second profile, the input to the NN model are the values for N1, N2 and FF from the 'unknown' flight data. The predicted values from the model for the output parameter EGT has been plotted along with the actual values of EGT from the flight data against N1 in Figure 4.

For the third profile, the input set to the NN model has the GS and TLA from the flight data and the predicted values from the model are for N1. Figure 5 shows the plot of these predicted values for N1 and the actual valus of N1 from the flight data with the Ground Speed.

For profile 4, the NN model takes the ALTITUDE, CAS and Gross Weight as input and predicts the values for N1. The plot for this Vs Altitude is shown in Figure 6.

From the plots it can be inferred that for all the four profiles, the differences between the predicted and the actual output values are within the acceptable limits. So the flight data used for the simulation can be said to be following the healthy trend laid down by the FCOM profiles.

The root mean square error found for each profile when simulated with more than 1000 data samples is given in Table 5. However the NN is being trained with voluminous data from the actual flight data having more than 50 sectors spread over more than 10 aircrafts flown across spatially distributed scenarios.

Table 5. RMSE for each profile

Profile	RMSE
Profile 1	1.534
Profile 2	3.569
Profile 3	2.817
Profile 4	1.579

6. CONCLUSION

The model developed is of a generic nature and can be used for monitoring flight data of any aircraft type with minor modifications, with respect to the identified FCOM profiles. The flight data of A320 family of aircrafts which has been used for simulation here shows that the data is following the recommended FCOM standards with minor deviations and is quite healthy as understood from the RMSE which is less than 5 for all the profiles.

Use of the neural network approach has resulted in fairly accurate predictions of the aircraft engine health indicator parameters and can be enhanced to incorporate more profiles and models. The refined system will be extremely helpful in ascertaining the health of the aircraft in order to trigger maintenance whenever required, irrespective of the maintenance schedule. This will definitely lead to safer flights and utmost usage of aircraft components. The use of dynamic feed-forward neural networks can be explored in future to assert its accuracy in the field of aircraft engine health monitoring.

The model will be enhanced with multiple profiles and predictive features for the health monitoring, health management and predictive maintenance. The network is planned to be integrated with the higher level Aircraft Integrated Vehicle Health Management System (IVHM) for whole aircraft level multi-system and sub-system health monitoring.

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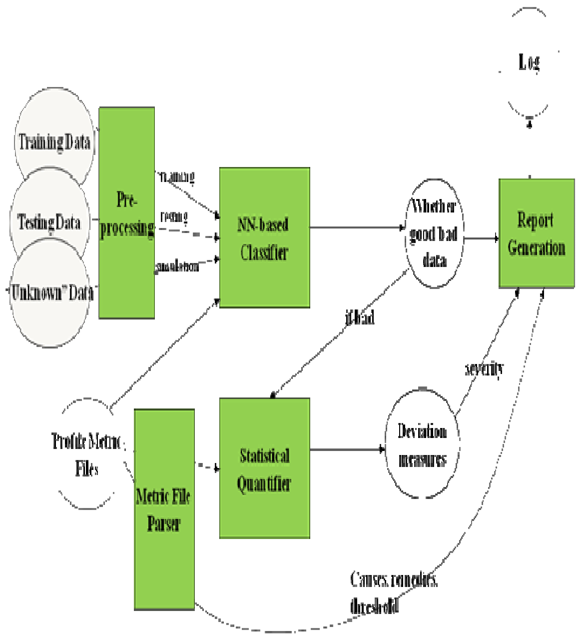

Figure 1. Architecture of the EHM System

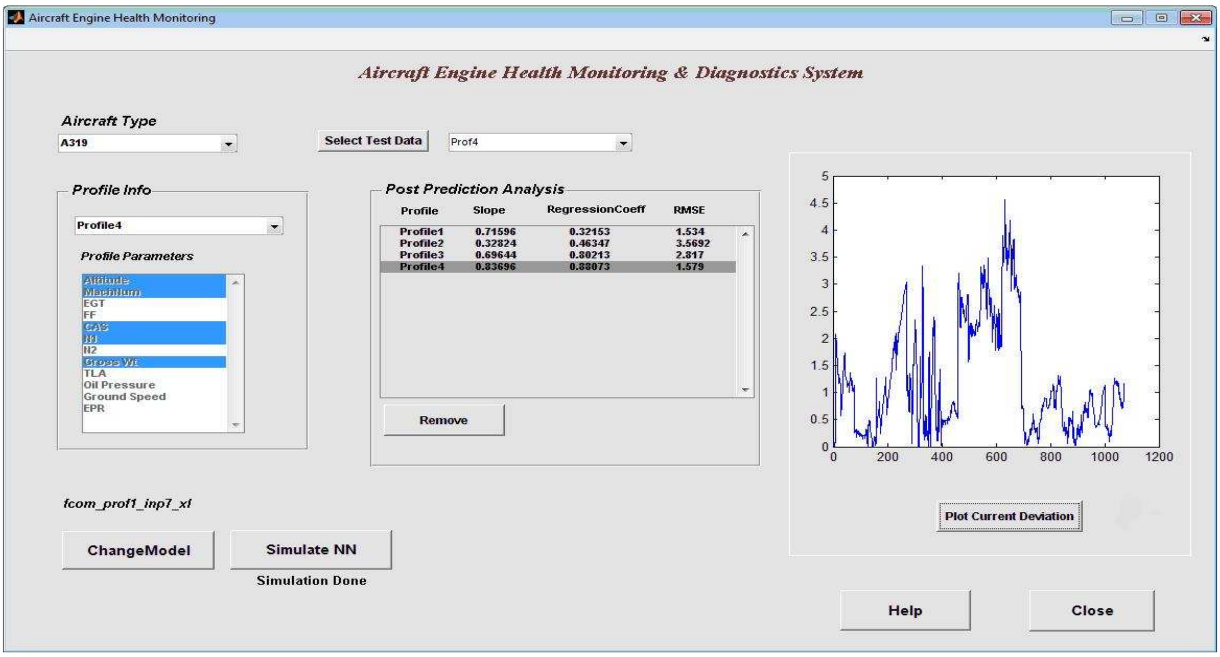

Figure 2. GUI of the EHM System

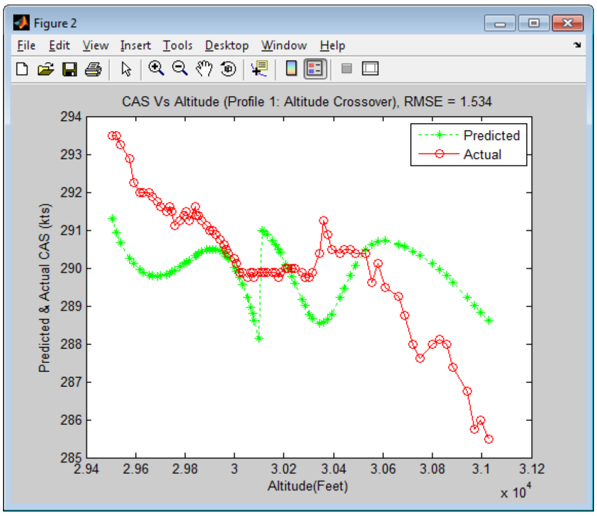

Figure 3. Profile 1-Predicted and Actual CAS Vs Altitude

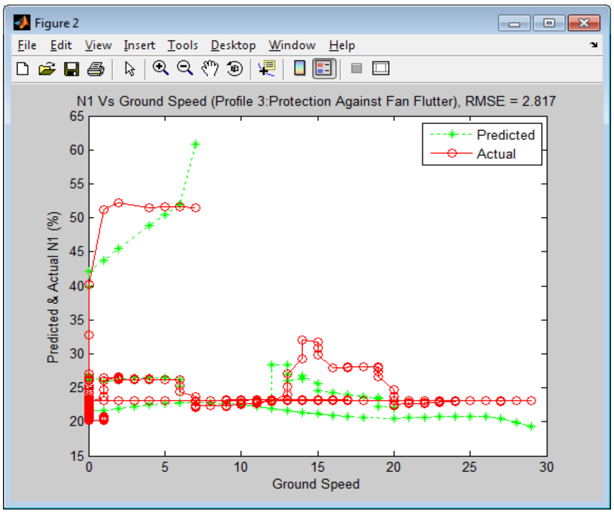

Figure 5. Profile 3 – Predicted and Actual N1 Vs GS

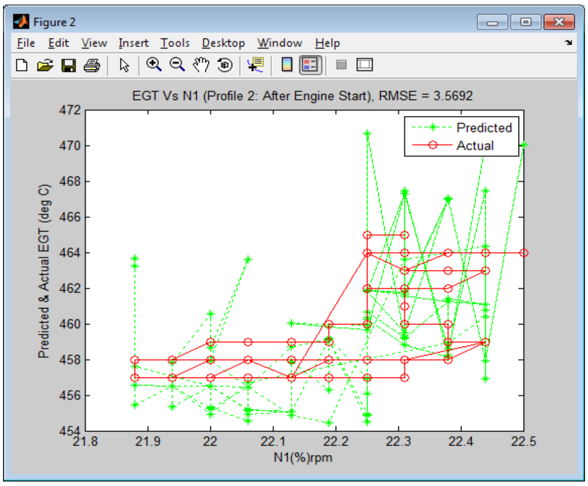

Figure 4. Profile 2 – Predicted and Actual EGT Vs N1

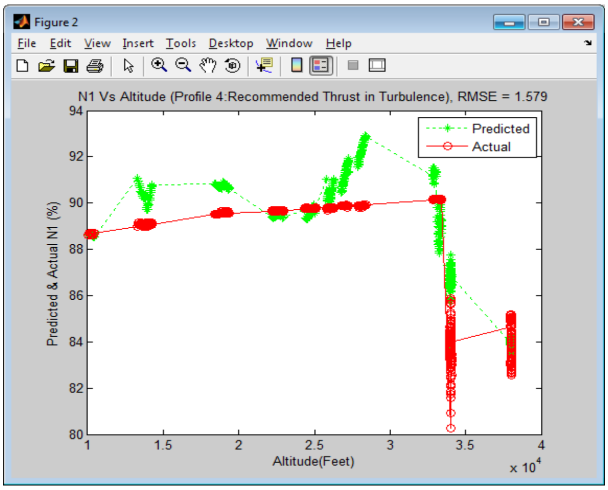

Figure 6. Profile 4 – Predicted and Actual N1 Vs Altitude